A meta-analysis of the investment-uncertainty relationship

Koetse, M.J.; de Groot, H.L.F.; Florax, R.J.G.M.

published in
Southern Economic Journal
2009

DOI (link to publisher)
10.4284/sej.2009.76.1.283

document version
Publisher's PDF, also known as Version of record

Southern Economic Journal 2009, 76(1), 283–306

A Meta-Analysis of the Investment-Uncertainty Relationship

Mark J. Koetse,* Henri L.F. de Groot,† and Raymond J.G.M. Florax‡

In this article we use meta-analysis to investigate the investment-uncertainty relationship. We focus on the direction and statistical significance of empirical estimates. Specifically, we estimate an ordered probit model and transform the estimated coefficients into marginal effects to reflect the changes in the probability of finding a significantly negative estimate, an insignificant estimate, or a significantly positive estimate. Exploratory data analysis shows that there is little empirical evidence for a positive relationship. The regression results suggest that the source of uncertainty, the level of data aggregation, the underlying model specification, and differences between short- and long-run effects are important sources of variation in study outcomes. These findings are, by and large, robust to the introduction of a trend variable to capture publication trends in the literature. The probability of finding a significantly negative relationship is higher in more recently published studies.

JEL Classification: D21, D80, E22

1. Introduction

The relationship between investment and uncertainty has been extensively analyzed in both the theoretical and the empirical literature since the 1970s. One of the most salient features of the theoretical literature is the inconclusiveness about the direction of the relationship. Early models can be found in Hartman (1972), Pindyck (1982), and Abel (1983), among others. Hartman (1972) uses a neoclassical model without capital stock adjustment costs and analyzes the relationship between capital productivity and uncertainty. Under the convexity of this relationship, and by Jensen's inequality, the incentive to produce and invest increases when uncertainty increases, implying a positive relationship. Hartman's model is, however, restricted to markets with perfect competition and relies on assumptions of constant returns to scale and substitutability of capital for other input factors. Also, adjustment costs are assumed to be symmetric. In real-world situations, however, this assumption is likely violated for most capital investments. Pindyck (1982) allows for asymmetric adjustment costs and argues that the effects of uncertainty on investment spending are in fact dependent on the characteristics of the

* VU University Amsterdam, Department of Spatial Economics, De Boelelaan 1105, 1081 HV, Amsterdam, the Netherlands; E-mail mkoetse@feweb.vu.nl; corresponding author.

† VU University Amsterdam and Tinbergen Institute, Department of Spatial Economics, De Boelelaan 1105, 1081 HV, Amsterdam, the Netherlands; E-mail hgroot@feweb.vu.nl.

‡ Purdue University, Department of Agricultural Economics, 403 West State Street, West Lafayette, IN 47907, USA, and VU University Amsterdam, Department of Spatial Economics; E-mail rflorax@purdue.edu.

This research was supported through the program "Stimulating the Adoption of Energy-Efficient Technologies," funded by the Netherlands Organization for Scientific Research (NWO) and the Dutch Ministry of Economic Affairs (SenterNovem). We are grateful to Tom Stanley, John Pepper, and two anonymous referees for useful comments on an earlier version of this article. The usual disclaimer applies.

Received June 2007; accepted September 2008.

adjustment cost function. Abel (1983) argues that increased uncertainty leads to increased investment spending, regardless of the characteristics of the adjustment cost function, effectively confirming the results of Hartman (1972). However, he also shows that adjustment costs matter for the relationship between investment and Tobin's Q. As a result, uncertainty has a direct effect on investment but also an indirect effect through Q in the Abel (1983) model. The overall effect is positive when adjustment costs are convex but is ambiguous when adjustment costs are concave.

More recent thinking about uncertainty is dominated by the concept of capital investment irreversibility (see Pindyck 1991; Dixit and Pindyck 1994). For a neoclassical model with asymmetric capital adjustment costs, that is, a certain degree of irreversibility of capital investment, Dixit and Pindyck show that an increase in uncertainty creates an option value of waiting for new information to arrive in the future. The central point of the irreversibility or real options literature is that an increase in uncertainty will *ceteris paribus* result in more investment projects being delayed. This argument has major implications for the timing of investment, implying that short-run investment levels may be affected but long-run investment levels will not. We can therefore distinguish between two general branches of research regarding the investment-uncertainty relationship: a first branch in which uncertainty is related to the timing of investment, and a second branch that analyzes the impact of uncertainty on the investment level.[1] This article focuses primarily on the second branch.

Given the ambiguity of the theoretical literature, there is no way to determine the direction of the relationship between investment and uncertainty *a priori*, let alone to draw inferences on the magnitude of the effect and its economic relevance. Various explanations for this ambiguity have been brought forward. One of the most obvious sources of heterogeneity is the degree of irreversibility of investment itself; that is, the smaller the possibilities to disinvest, the larger the negative impact of uncertainty on investment spending. A similar argument holds for risk aversion.[2] Numerous attempts have been made to resolve this issue empirically, but these attempts seem to have added to, rather than resolved, the existing ambiguity. In Carruth, Dickerson, and Henley (2000) an excellent overview is provided of the most relevant topics in the theoretical debate on the investment-uncertainty relationship. Major issues in the empirical literature are also discussed, such as the possible consequences of data aggregation and the differences between operational measures of uncertainty. However, although the Carruth, Dickerson, and Henley (2000) study is obviously useful and important in its own right, it is qualitative in nature and does not attempt to quantify the importance of differences in study characteristics for the variation in study outcomes.

---

[1] For theoretical studies that try to unify the timing and level effects of uncertainty, see Abel and Eberly (1999) and Bar-Ilan and Strange (1999). The former argue that, under irreversibility, there is a so-called hangover effect. This results from the fact that when the marginal revenue product of capital is low, a firm would like to sell some of its already installed capital but cannot do so because investment is irreversible. In this case, the desired stock of capital is lower than the actual stock. Since under reversible investment the actual capital stock can be instantaneously adjusted to the desired level, the actual capital stock is higher under irreversibility than under reversibility when capital productivity is low (see Bo 2006 for an empirical analysis). Under uncertainty this effect is reinforced.

[2] For theoretical contributions on the role of risk aversion see Nakamura (1999) and Saltari and Ticchi (2005). Other factors that may affect the direction and magnitude of the relationship are underlying market structure (Hartman 1972; Abel 1983; Caballero 1991; Kulatilaka and Perotti 1998), the discrepancy between industry-level and firm-specific idiosyncratic uncertainty (Pindyck 1993), and financial conditions of the firm (Ghosal and Loungani 2000; Peeters 2001).

In this article we therefore perform a meta-analysis on the relationship between uncertainty and investment spending. Meta-analysis is a form of quantitative research synthesis originally developed in experimental medicine and later extended to fields such as biomedicine and experimental behavioral sciences, specifically education and psychology. During the last two decades it has also been widely applied in economics.[3] The intuitive appeal of meta-analysis rests on its ability to combine sometimes widely scattered empirical evidence on a certain topic and the associated increase in statistical power of hypothesis testing when combining independent research results. Moreover, by controlling for variations in characteristics across studies, meta-analysis provides quantitative insight into which factors are relevant in explaining the variation in study outcomes. As such, meta-analysis provides a quantitative analytic assessment in addition to the more qualitative judgment provided by a narrative literature review (Stanley 2001).

The remainder of this article is organized as follows: Section 2 discusses the type of estimates used in this study, as well as the way in which they have been sampled from the literature. We also provide descriptive statistics for the resulting meta-sample. Section 3 discusses the operationalization of moderator variables, which represent differences in study characteristics that may systematically affect a study's outcome. The model and estimation procedure are presented in section 4, while section 5 discusses the estimation results. Section 6 concludes.

2. Effect Size, Sampling Procedure, and Sample Characteristics

Empirical studies on investment behavior are heterogeneous in many respects. Studies generally include a wide variety of explanatory variables; they operationalize investment and uncertainty in different ways; and they are performed on samples that vary over time and space. The impact of these sources of heterogeneity will be assessed in the meta-regression analysis. An important observation is that the investment-uncertainty literature is focused on the sign of the relationship and not on its magnitude. In order to focus on the main issue in the literature we define an effect size that does not include the magnitude of the relationship. In our attempt to create a sample of effect sizes that included the magnitude of the relationship we faced several restrictions, the most important being that most of the study results are not defined in a common, scale-free metric. In the empirical literature, three different functional forms are used in primary studies: linear, semilogarithmic, and double-log specifications. Coefficients from double-log models can be interpreted as elasticities, which is generally a good measure for an effect size. Coefficients from linear and semilogarithmic models, however, are not scale-free, implying that results from these studies are incomparable and that a transformation into elasticities is necessary. This was only feasible for a limited subset of linear and semilog coefficients, implying that the resulting sample of elasticities would be substantially smaller than the original sample of study results. In order to use the full sample of study results, while still focusing on the main issue in the literature, we focus on the direction and statistical

[3] For recent developments in the literature see, for example, Roberts and Stanley (2005). Good examples of empirical applications of meta-analysis in macroeconomics are Stanley (1998); Poot (2000); Djankov and Murrell (2002); de Mooij and Ederveen (2003); Nijkamp and Poot (2004); Abreu, de Groot, and Florax (2005); Rose and Stanley (2005); Weichselbaumer and Winter-Ebmer (2005); and de Dominicis, Florax, and de Groot (2008).

significance of the estimates rather than on the magnitude of the elasticities. In our empirical analysis we ultimately distinguish between significantly negative, insignificant, and significantly positive study results.

In creating our sample of studies we first searched through titles and abstracts of studies using keywords in standard online search engines such as Econlit, Picarta, and RePEc. Keywords used were "investment," "uncertainty," and "volatility." We subsequently looked for papers and articles in the reference lists of studies that were collected. Ultimately, we collected 48 studies that empirically analyze the relationship between uncertainty and investment. These studies provided a total of 957 estimates, but some studies and estimates had to be excluded from the database for one of the following reasons. First, as suggested by Abel and Eberly (1999), among others, one of the potential reasons for the theoretical ambiguity on the direction of the relationship is that the relationship is potentially hump shaped.[4] Two studies in our sample use a model specification in which uncertainty is included in a linear and a quadratic fashion to test this hypothesis (Lensink 2002; Bo and Lensink 2005).[5] In these studies, the effect of uncertainty on investment is conditional on the degree of uncertainty. We therefore excluded these observations from the analysis (32 estimates). Second, some studies use a logit or probit model to estimate the relationship. In these models the dependent variable is either binary or ordered; that is, the analysis is concerned with estimating the impact of factors determining the probability that investment actually takes place. As such, the results from these models do not provide information on the change in the level of investment and are therefore excluded from the analysis (59 estimates). Third, standard errors or t-statistics are essential for constructing our dependent variable, since they are used to calculate the p-values (statistical significance) of study estimates. We exclude the estimates for which no standard errors or t statistics were provided in the study (24 estimates). Fourth, some models provide information on the relationship between investment and an uncertainty measure that was interacted with another variable. For these models either the isolated effect of uncertainty on investment could not be extracted, or standard errors for the isolated effect could not be obtained. These estimates are therefore excluded (32 estimates). Finally, some studies use alternative dependent variables, such as the capital-to-labor ratio (Ghosal 1991, 1995; Green, Lensink, and Murinde 2001) or the investment lag (Favero, Pesaran, and Sharma 1994; Hurn and Wright 1994). The former studies provide interesting insights on factor demand under uncertainty but provide little direct evidence on investment behavior, and they are therefore omitted (23 estimates). The latter studies measure the delay of investment instead of the effect on the investment level, and although this provides interesting insights, the outcomes of these studies are incomparable to the outcomes of other empirical studies in our meta-analysis (20 estimates).

[4] One of the arguments for such a pattern is potential risk-seeking behavior of economic agents over the domain of small losses (Kahneman and Tversky 1979). An increase in uncertainty implies an increase in the trigger value of investment, but it also increases the probability of hitting this trigger value. Although it is generally assumed that the former effect dominates, the reverse may be true for low levels of uncertainty. Another possibility is that firms react differently to positive and negative shocks, where the inverted U-curve stems from the notion that negative shocks are generally associated with high uncertainty (Bo 2001, p. 100).

[5] The main conclusion from these studies is that uncertainty indeed has a positive effect on investment spending for low levels of uncertainty and a negative effect for high levels, thereby providing evidence for a nonlinear investment-uncertainty relationship.

Table 1. Descriptive Statistics on Sign of the Investment-Uncertainty Estimates and Their Statistical Significance Using a 5% Critical Significance Level ($N = 767$)

Sign	Significance	Count	Percentage (%)	Count	Percentage (%)
Negative	Significant	225	30	505	66
	Insignificant	280	37		
Positive	Insignificant	232	30	262	34
	Significant	30	4		
Total		767	100	767	100

Ultimately, we arrive at a sample of 767 observations taken from 36 different studies (studies are included in the References section, denoted by ■). In Appendix 1 we provide details of each study included in the meta-analysis. Table 1 presents descriptive statistics of the sample. The table shows that 66% of the estimates are negative. When a distinction is made between statistically significant and insignificant results, using a critical significance level of 5%, the number of insignificant negative results is of the same order of magnitude as the number of insignificant positive results. However, a significantly negative relationship is observed quite frequently (30%), while very few observations actually find a significantly positive relationship between investment and uncertainty (4%). Interestingly, the positive estimates (30 in total) are taken from nine different studies that differ widely in terms of, for instance, data type, region, time period, and sample size.

3. Operationalization of Moderator Variables

This section discusses several dimensions along which the studies that have been included in our analysis differ. We discuss the measure of investment that has been used, the uncertainty measure, control variables, data characteristics, spatial and temporal data characteristics, and estimation technique. This provides the basis for our meta-regression model specification.

Measures of Investment

Most studies use aggregate investment figures, implying that the type of investment is fairly homogeneous across studies. Investment is specified in three distinct ways: unscaled investment, investment scaled by some measure of income (sales, gross domestic product [GDP]), and investment scaled by capital. It is not always clear *a priori* why and in what way measurement differences affect study outcomes. For example, in a period of increased uncertainty a firm may decrease investment even further when it also considers its existing capital stock to be too large (see the hangover effect discussed in footnote 1). This effect may have a bigger impact on the outcomes of studies that use investment-to-capital ratios than on outcomes of studies that use unscaled investment because in the former case the decrease in investment is measured as a fraction of a capital stock that is already considered too high. The effect of uncertainty on investment will still have the same direction for both investment measures but may seem larger *in magnitude* for studies that use the investment-to-capital ratio. This may systematically affect the statistical significance of study outcomes, and as such it may show up in our regression results.

Sources and Measures of Uncertainty

The source of uncertainty is heterogeneous across studies. We distinguish seven sources of uncertainty: uncertainty of sales/demand/output, profit, output prices, input prices, inflation, exchange rates, stock prices, and a rest category with variables such as uncertainty of government expenditures. It is interesting to see whether these uncertainty differences have an impact.[6] We explicitly control for the fact that in many studies multiple uncertainty sources were included in the model specification.

There is no clear consensus in the literature on how to construct a good proxy for uncertainty, mainly because the method of measuring uncertainty is associated with assumptions regarding the expectation formation process of decision makers. As a consequence, several measures of uncertainty are used. Most of the empirical studies on the investment-uncertainty relationship use historical data on the variable under investigation to create an uncertainty proxy. However, since uncertainty is fundamentally a forward-looking phenomenon, historical data are flawed. A popular approach to measure forward-looking uncertainty is to ask entrepreneurs or economists for their subjective evaluations of uncertainty. Five of the articles in our sample use such a subjective uncertainty measure, avoiding the inherent theoretical problems associated with historical data. For example, Pattillo (1998) and Lensink, van der Steen, and Sterken (2005) use a survey in which they ask entrepreneurs to give a probability distribution of the development of expected sales over a certain time period.[7] Such a measure comes closest to the ideal measure of an individual's perceived uncertainty. In our model we account for the difference between studies that use backward-looking historical data and studies that use forward-looking subjective evaluations of uncertainty.

Control Variables in Primary Models

Empirical studies on investment can roughly be classified into two groups according to the underlying theoretical models. The first model, discussed extensively in Jorgenson (1971), is the accelerator model of investment. In this model investment spending is driven by income or sales. These models include sales or GDP as an explanatory variable. The second investment model is the Q model of investment. In this model investment takes place if Tobin's marginal Q, the ratio of the marginal value of capital and the market price of capital, is larger than 1 (see Tobin 1969; Cuthbertson and Gasparro 1995). Since stock prices, and therefore Q, reflect expected future profits, the Q model has an additional feature above and beyond the standard neoclassical investment model in that it incorporates expected future profits into current investment decisions. Since Q represents the market value of capital it should, in principle, incorporate the effects of uncertainty. It is therefore interesting to check whether explicitly accounting for uncertainty has power in explaining investment behavior above and beyond Q.[8]

Apart from the two different types of investment models, there is substantial variation in the control variables used in the underlying primary studies. Several studies include one or more of the following: wages and capital prices, a time trend, debt position, stock prices, size of a firm, government expenditures, a lagged dependent variable to control for autocorrelation,

---

[6] For empirical analyses on the differential impact of different sources of uncertainty see Huizinga (1993) and Koetse, van der Vlist, and de Groot (2006).

[7] See Driver and Moreton (1991) and Ferderer (1993a) for alternative measurements of subjective uncertainty.

[8] See Bo (2001), among others, for an extensive discussion and empirical investigation of this issue.

and trade flows. Since the explanatory variables are used in different combinations, we cannot distinguish between well-defined empirical models and instead resort to including dummy variables for each of these explanatory variables in the meta-regression model.

Data Characteristics

An interesting difference in data characteristics across studies pertains to the distinction between industry-wide and idiosyncratic firm-level uncertainty. In the models by Abel (1983) and Caballero (1991), idiosyncratic uncertainty has a positive effect on investment for firms with constant returns to scale technology, operating in a competitive environment. Pindyck (1993) argues that if uncertainty is identical for all firms in an industry, it will be more difficult to disinvest than if only a single firm experiences increased uncertainty. He subsequently shows that, under identical technology and market conditions, industry-wide uncertainty has a negative impact on investment spending. However, under alternative assumptions, idiosyncratic uncertainty may be just as important for investment decisions. In fact, in an empirical analysis using firm-level data, Bo (2002) finds that idiosyncratic uncertainty has a negative impact on investment and that it is more important than industry-wide uncertainty. Because of measurement difficulties, empirical studies that distinguish explicitly between industry-wide and firm-level uncertainty are scarce. In the meta-regression analysis the effects may be picked up by differences in the level of data aggregation. However, differences in data aggregation may also have other effects on study outcomes, which may obscure the differential effects of industry-wide and idiosyncratic uncertainty.

Another distinction in data characteristics concerns the difference between time-series, panel, and cross-section data. Time-series data typically reflect short-run changes, while cross-section data are generally perceived to identify long-run changes. The effect of panel data is expected to be closer to the short-run effect, the intuition being that fixed or random effects in a panel data model will generally control for differences between countries, regions, or industries and firms, thereby likely picking up at least part of the longer term effects. The distinction between different types of data in the meta-regression analysis will therefore shed light on differences between short- and long-run effects of uncertainty on investment.

Spatial, Temporal, and Econometric Issues

Regional differences across studies may reflect differences in, for instance, sector composition, the degree of competition, institutional setting, the functioning of capital markets, and culturally determined risk aversion. Since many studies use data from several countries and from several parts of the world, a clear distinction between, for instance, the United States and Europe, cannot be made. The only clear distinction is between developed and less developed countries. Furthermore, in order to control for differences in the time period used in an underlying study we construct a time trend based on the median year of the sample data in the underlying studies.[9] Finally, we distinguish between studies that use ordinary least squares (OLS) or more sophisticated estimation techniques and control for studies that correct for possible endogeneity by using instrumental variables.

---

[9] The trend variable is rescaled and equals unity for 1970.

Remaining Sources of Variation

Clearly, some sources of heterogeneity cannot be accounted for in the meta-regression analysis. For example, potential control variables for the investment-uncertainty relationship in underlying studies are the degree of irreversibility of investment, the degree of risk aversion, and assumptions with respect to substitution possibilities between production factors. However, most of the empirical studies do not provide explicit information on these issues. The only possible way to account for these sources of heterogeneity is by including fixed effects for specific sectors with different characteristics on the abovementioned dimensions. A practical difficulty here is that most studies that use sector-level data do so for the entire manufacturing sector, implying that very little sectoral variation is present in the set of underlying studies. Sector-specific fixed effects are therefore not included in the meta-regression model, and part of the heterogeneity in the sample is likely left unexplained. However, the fact that most studies use aggregate manufacturing data has a potential advantage as well. Within a single study, sectoral variation may be substantial, but since most studies use comparable data, sectoral differences between studies are likely small.

4. Model and Estimation Procedure

In the meta-regression model we distinguish between significantly negative, insignificant, and significantly positive estimates using a categorical effect size indicator as the dependent variable. The categories are labeled 0, 1, and 2, respectively, using a 5% critical significance level. The model that is generally applied in a meta-analysis with a categorical effect size with more than two ordered categories is the ordered probit model.[10] In estimating this model we have to deal with the fact that multiple estimates are derived from a single study. As shown by Bijmolt and Pieters (2001), a good way to deal with this is to estimate a model with equal weights per study in which each observation is weighted with the inverse of the total number of estimates that is drawn from the same study (see Bijmolt and Pieters 2001). This procedure prevents studies with a large number of estimates from having a disproportionally large influence on the estimation results.

Because the ordered probit results reveal the direction of change rather than the absolute magnitude of changes in observing an effect in one of the three categories, we transform the ordered probit coefficients into marginal effects. This implies that for each of the explanatory variables in our model we calculate the change in the probability of obtaining a significantly negative, an insignificant, and a significantly positive estimate.[11] Almost all explanatory variables are dummy variables, for which marginal effects are obtained by considering a shift in

[10] A disadvantage of using a categorical variable is that it discards some of the information on the statistical significance of the effect. An alternative approach that does make use of all the available information is a regression on z values. This approach also allows for the calculation of marginal effects, so the results are comparable to those obtained using an ordered probit analysis. The patterns and findings from this analysis are very similar to those presented here. The most striking difference is that the marginal effects for the third category, that is, significantly positive estimates, are substantially smaller (for details see Koetse, de Groot, and Florax 2006).

[11] It is of course possible to distinguish between four or more categories. For example, we could make a further distinction between insignificant negative and insignificant positive study outcomes, but we could also use sample quartiles or deciles. However, for reasons of tractability and exposition we choose to work with three categories.

the dummy value from 0 to 1, keeping the other explanatory variables (dummy variables included) constant at their respective means. Since standard errors of the computed marginal effects are not readily available, they are obtained by linear approximation using the delta method (Greene 2003, pp. 674–675).[12]

A relevant issue in meta-analysis is publication bias, and preferably remedial devices should be used to avoid spurious results (see the contributions in Roberts and Stanley 2005). However, existing methods to detect and correct for potential publication bias, such as Hedges' weighted distribution theory (Hedges 1992) and the meta-regression methods developed by Stanley (2008), have been developed for effect sizes defined on a ratio scale. The use of standard errors in defining a categorical effect size indicator in our meta-regression model precludes use of these techniques. We therefore mitigate the potential influence of publication bias by including the year of publication in our model specification.[13] Since we also include the average year of the sample used in a study, the aim here is to correct for a possible publication time trend (see Goldfarb 1995). Potentially problematic, however, is the high correlation coefficient between the two time trend variables ($r = 0.68$). Ultimately, we present two separate models: a model with and a model without publication year among the explanatory variables.[14]

5. Estimation Results

The ordered probit estimates and associated marginal effects of the model without the publication time trend variable (model 1) are presented in Table 2. Regarding the measurement of investment, there is a clear difference in study outcomes between studies that use an investment-to-capital ratio and studies that use the investment level (the omitted category in the meta-regression) or the investment-to-sales ratio. Studies that use the investment-to-capital ratio are characterized by a relatively high probability of finding a significantly negative result. The only difference between these measures is the presence (or absence) of capital in the denominator. The explanation is therefore most likely related to the impact of uncertainty on the capital stock. In general, however, it is unlikely that uncertainty influences the capital stock in the short run, which means that the result is most probably due to a measurement-related issue, which may range from error in the measurement of the capital stock to some statistical artifact. In either case, studies using the investment level or investment-to-sales ratio as the dependent variable should be preferred to those that use the investment-to-capital ratio.

---

[12] A detailed description of the calculation of standard errors is available upon request from the authors.

[13] The publication trend variable is rescaled and equals unity for 1989.

[14] In a variant not included here for reasons of space, we also controlled for differences in publication quality (see Rosenberger and Stanley 2006). Creating a continuous measure based on impact factors was not possible since impact factors are not available for working papers and some of the journals. Furthermore, there are only two working papers in our sample, making a distinction between working papers and journal articles unviable. We therefore created dummy variables based on a categorical ranking of journals used by the Tinbergen Institute (see www.tinbergen.nl). We distinguish between *A*, *B,* and *C* publications, where the *C* category consists of working papers and journals that are not included in the *A* or *B* category. The results turn out not to be strictly increasing or decreasing in terms of quality of the publication outlet: *A* publications produce more insignificant estimates than *C* publications, while *B* publications produce more significantly negative estimates. The results documented in the main text are, however, robust to the inclusion of the publication quality dummy variables. Results for this alternative specification are available upon request from the authors.

Table 2. Estimates and Associated Marginal Effects of Meta-Analysis Ordered Probit Model 1 (Standard Errors in Parentheses)

		Marginal Effects Model 1		
	Ordered Probit Model 1	Significantly Negative	Insignificant	Significantly Positive
Constant	0.142	—	—	—
	(0.379)			
Investment measures				
Investment-to-sales ratio[a]	−0.151	0.056	−0.049	−0.007
	(0.230)	(0.087)	(0.077)	(0.011)
Investment-to-capital ratio[a]	−0.791**	0.295**	−0.257**	−0.038**
	(0.223)	(0.081)	(0.072)	(0.012)
Sources and measures of uncertainty				
Input price uncertainty[b]	0.402	−0.136	0.106	0.030
	(0.326)	(0.099)	(0.066)	(0.034)
Sales uncertainty[b]	−0.019	0.007	−0.006	−0.001
	(0.285)	(0.106)	(0.091)	(0.015)
Stock price uncertainty[b]	1.077**	−0.302**	0.170**	0.132*
	(0.302)	(0.057)	(0.034)	(0.066)
Profit uncertainty[b]	0.490	−0.162	0.123	0.040
	(0.362)	(0.104)	(0.064)	(0.042)
Inflation rate uncertainty[b]	0.936**	−0.271**	0.163**	0.107
	(0.310)	(0.062)	(0.028)	(0.062)
Exchange rate uncertainty[b]	0.660*	−0.226*	0.178*	0.048
	(0.336)	(0.103)	(0.072)	(0.034)
Other uncertainty sources[b]	0.422	−0.143	0.112	0.032
	(0.319)	(0.097)	(0.066)	(0.032)
Joint estimation[c]	0.876**	−0.309**	0.253**	0.056**
	(0.170)	(0.054)	(0.041)	(0.017)
Subjective uncertainty[d]	0.371	−0.127	0.099	0.027
	(0.328)	(0.102)	(0.072)	(0.031)
Control variables in primary models[e]				
Tobin's Q included	−0.569*	0.221*	−0.202*	−0.019**
	(0.229)	(0.090)	(0.085)	(0.006)
Accelerator variable included	−0.573**	0.195**	−0.152**	−0.043*
	(0.153)	(0.047)	(0.033)	(0.017)
Wages included	−0.531	0.207	−0.189	−0.018*
	(0.323)	(0.128)	(0.121)	(0.007)

Table 2. Continued.

		Marginal Effects Model 1		
	Ordered Probit Model 1	Significantly Negative	Insignificant	Significantly Positive
Capital price included	−0.058	0.021	−0.019	−0.003
	(0.230)	(0.087)	(0.075)	(0.011)
Time trend included	0.454*	−0.161*	0.131*	0.029
	(0.193)	(0.065)	(0.051)	(0.015)
Debt position included	0.639**	−0.204**	0.146**	0.058
	(0.219)	(0.059)	(0.034)	(0.030)
Stock price included	−1.434*	0.505**	−0.482**	−0.023**
	(0.596)	(0.141)	(0.139)	(0.004)
Size of firm included	0.167	−0.059	0.049	0.010
	(0.311)	(0.107)	(0.084)	(0.022)
Government expenditures included	−0.387	0.150	−0.135	−0.015
	(0.287)	(0.114)	(0.106)	(0.008)
Dependent lag included	−0.348*	0.131*	−0.114*	−0.017*
	(0.167)	(0.064)	(0.056)	(0.008)
Trade flows included	−0.048	0.018	−0.015	−0.003
	(0.261)	(0.097)	(0.084)	(0.013)
Data characteristics—aggregation level				
Industry-level data[f]	0.854**	−0.304**	0.252**	0.052*
	(0.231)	(0.075)	(0.058)	(0.020)
Firm-level data[f]	1.130**	−0.358**	0.254**	0.104*
	(0.261)	(0.065)	(0.036)	(0.042)
Data characteristics—time series vs. cross section				
Panel data[g]	0.728**	−0.240**	0.180**	0.060
	(0.261)	(0.076)	(0.048)	(0.031)
Cross-section data[g]	0.672**	−0.234**	0.188**	0.046*
	(0.238)	(0.078)	(0.059)	(0.021)
Spatial, temporal, and econometric issues				
Average year of sample	−0.025	0.009	−0.008	−0.001
	(0.018)	(0.007)	(0.006)	(0.001)
Year of publication	—	—	—	—
Less developed countries[h]	0.069	−0.025	0.022	0.004
	(0.182)	(0.066)	(0.055)	(0.011)

Table 2. Continued.

	Ordered Probit Model 1	Marginal Effects Model 1		
		Significantly Negative	Insignificant	Significantly Positive
OLS estimation[i]	−0.310*	0.109*	−0.089*	−0.020
	(0.156)	(0.053)	(0.041)	(0.012)
Instrumental variables estimation[j]	−0.723**	0.263**	−0.223**	−0.040**
	(0.189)	(0.068)	(0.058)	(0.013)
Number of observations	767			
Prob (chi-squared)	0.000			
Log-likelihood	−516.8			
Log-likelihood restricted	−578.1			

[a] Reference category: Unscaled investment.
[b] Reference category: Output price uncertainty.
[c] Reference category: No joint estimation.
[d] Reference category: Objective or backward-looking uncertainty.
[e] Reference category: Explanatory variable is excluded from the primary study model.
[f] Reference category: Country-level data.
[g] Reference category: Time-series data.
[h] Reference category: Developed countries.
[i] Reference category: Estimation other than OLS.
[j] Reference category: No instrumental variables estimation.
* $p < 0.05$.
** $p < 0.01$.

Considering the uncertainty measure used, there is a dividing line between studies that use output price uncertainty (the reference category) or sales uncertainty and the other uncertainty measures. Studies using other sources of uncertainty tend to be characterized by a relatively small probability of finding a significantly negative outcome. The marginal effects of stock price uncertainty, inflation rate uncertainty, and exchange rate uncertainty stand out in terms of magnitude and statistical significance; they increase the probability of finding an insignificant effect by 20–30%. Using stock price uncertainty furthermore substantially increases the probability of finding a significantly positive estimate. Theory states little about the impact of different sources of uncertainty, so the relevant question is whether the estimates on the different sources of uncertainty represent true underlying economic patterns or whether they in fact all represent the same underlying generic uncertainty that is present in an economy. In the latter case the differences in estimates may occur because some sources capture this fundamental uncertainty better than others. Our results do not point to either interpretation. Strikingly, however, the three sources that stand out (stock price, inflation, and exchange rate uncertainty) are clearly more related to macroeconomic processes than the other sources (sales, output price, input price, and profit uncertainty), which are more related to firm- or industry-specific processes. Moreover, fluctuations in stock prices are to a large extent influenced by macroeconomic fluctuations. The associated interpretation of the results would then be that uncertainty from macroeconomic fluctuations matters less than uncertainty from industry- or firm-specific fluctuations. Although the latter are, of course, influenced by processes at the macroeconomic level, it is likely that they better represent the uncertainty that is relevant for individual investment decisions. Further, when the impact of various sources of uncertainty is estimated simultaneously, the probability of finding an insignificant result increases. This result makes sense if the uncertainty proxies are correlated, in which case including each measure in isolation would produce, on average, more statistically significant estimates of the relationship under investigation. Finally, the results show that using a subjective forward-looking uncertainty measure instead of a backward-looking uncertainty measure (which is the reference category) has a small and statistically insignificant effect.

With respect to model specification, it has been argued that uncertainty can be captured by Tobin's Q (the shadow value of capital), making it unnecessary to explicitly account for uncertainty in investment models. Our findings, however, suggest the opposite: using a Q model actually increases the probability of finding a significantly negative impact of uncertainty on investment spending by approximately 20%. Ultimately we do not know the true underlying investment model, which makes the interpretation of this result ambiguous. If the true underlying investment-uncertainty relationship is negative, the result suggests that Tobin's Q not only fails to incorporate the full impact of uncertainty on investment spending, but that its exclusion from a model specification may even obfuscate a negative relationship. If the true relationship is that uncertainty does not affect investment spending, the result suggests that Tobin's Q increases the probability of a type I error. Not including an accelerator variable, wages, and capital prices in a model specification has a similar effect; although, the effects of wages and capital prices are statistically insignificant. Various other explanatory variables in the underlying studies appear to be important as well. The impact of including stock prices in the model substantially increases the probability of obtaining a significantly negative outcome. These findings reveal potentially important sources of bias and have clear implications for model building in future empirical research.

Similar to differences in model specification, the level of data aggregation is an issue that is of relevance in most meta-analyses in economics. In our case, studies using industry- and firm-level data produce around 30–35% fewer statistically significant negative estimates than studies that use country-level data (the omitted category in the analysis). Differences in investment between countries depend to a certain extent on issues that are difficult to account for in a model, such as institutional settings, culture-related risk attitudes, and functioning of second-hand markets. It is therefore likely that models based on country-level data are misspecified and produce estimates that are off the mark. Moreover, since the effect of uncertainty on investment spending is a microeconomic phenomenon, the results from studies that use sector- or firm-level data are generally preferable to those that use country-level data. In this respect, we find evidence that industry-wide studies find more negative results than firm-specific studies. The differences, however, are small. Insofar as these differences reflect differences between industry-wide and firm-specific uncertainty, the results provide some evidence for the claim made in Pindyck (1993) that under industry-wide uncertainty the possibilities to disinvest are smaller than under firm-specific uncertainty, leading to a more negative relationship.

Studies that use panel and cross-section data produce more insignificant estimates (around 20%) than studies that use time-series data (the omitted category). A difference between these data types is that cross-section data are better at capturing long-run effects, while time-series data measure the short-run impact. Our findings therefore suggest that the impact of uncertainty on investment spending is negative in the short run but fades out as time progresses.[15]

Finally, the effects of different econometric estimators appear to be nontrivial. OLS studies display a slightly higher probability to produce a significantly negative result than studies that use more sophisticated estimation techniques. A similar but much stronger effect is found for studies that control for endogeneity, implying that not taking this issue into account very likely produces an estimate that is off the mark, at least in terms of sign and statistical significance. The relationship between uncertainty and investment also appears to have been constant over the years, as shown by the small and statistically insignificant marginal effects on the *average year of sample* variable, and there appear to be no differences between developed and less developed countries. The latter is somewhat surprising, since one might have expected that firms in less developed countries have more difficulty in coping with uncertainty, for instance, because they do not have the same possibilities to hedge against or deal with uncertainty. Differences in specialization and functioning of second-hand markets may, however, counteract this effect.

In Table 3 we present the ordered probit estimates and associated marginal effects of the model that includes the publication time trend variable (model 2). The results suggest that the odds of finding a significantly negative estimate are higher for more recent studies (*year of publication*), while the actual underlying relationship has become more insignificant over the years (*average year of sample*). The latter may reflect a true trend in the relationship, which can be explained by better functioning of second-hand markets, which makes disinvestment of

[15] Although one would expect panel data to pick up only some of the long-run effects of uncertainty, the results show that the effect of panel data is actually stronger than that of cross-section data. However, the difference is very small, and statistically we cannot reject the hypothesis that the coefficients are equal at the usual significance levels. This holds for the marginal effects as well.

Table 3. Estimates and Associated Marginal Effects of Meta-Analysis Ordered Probit Model 2 (Standard Errors in Parentheses)[a]

		Marginal Effects Model 2		
	Ordered Probit Model 2	Significantly Negative	Insignificant	Significantly Positive
Constant	0.962*	—	—	—
	(0.406)			
Investment measures				
Investment-to-sales ratio	−0.050	0.018	−0.016	−0.002
	(0.240)	(0.086)	(0.077)	(0.009)
Investment-to-capital ratio	−0.789**	0.284**	−0.256**	−0.028**
	(0.230)	(0.082)	(0.075)	(0.010)
Sources and measures of uncertainty				
Input price uncertainty	0.439	−0.138	0.112	0.026
	(0.340)	(0.092)	(0.064)	(0.029)
Sales uncertainty	−0.244	0.089	−0.081	−0.008
	(0.295)	(0.111)	(0.103)	(0.008)
Stock price uncertainty	1.311**	−0.312**	0.159**	0.153*
	(0.315)	(0.045)	(0.053)	(0.074)
Profit uncertainty	1.876**	−0.350**	0.023	0.326*
	(0.413)	(0.035)	(0.134)	(0.146)
Inflation rate uncertainty	0.582	−0.176*	0.137**	0.039
	(0.323)	(0.079)	(0.048)	(0.034)
Exchange rate uncertainty	0.298	−0.102	0.088	0.014
	(0.348)	(0.114)	(0.096)	(0.019)
Other uncertainty sources	−0.002	0.001	−0.001	0.000
	(0.334)	(0.118)	(0.105)	(0.013)
Joint estimation	0.926**	−0.310**	0.264**	0.046**
	(0.175)	(0.052)	(0.042)	(0.015)
Subjective uncertainty	0.199	−0.067	0.058	0.009
	(0.339)	(0.109)	(0.090)	(0.019)
Control variables in primary models				
Tobin's Q included	−0.530*	0.202*	−0.189*	−0.013**
	(0.237)	(0.094)	(0.090)	(0.004)
Accelerator variable included	−0.304	0.102*	−0.088*	−0.014
	(0.161)	(0.051)	(0.043)	(0.010)

Table 3. Continued.

	Ordered Probit Model 2	Marginal Effects Model 2		
		Significantly Negative	Insignificant	Significantly Positive
Wages included	−0.363	0.136	−0.126	−0.010
	(0.336)	(0.132)	(0.125)	(0.007)
Capital price included	−0.397	0.149	−0.137	−0.011*
	(0.238)	(0.093)	(0.088)	(0.005)
Time trend included	0.704**	−0.228**	0.189**	0.039*
	(0.204)	(0.061)	(0.048)	(0.016)
Debt position included	0.488*	−0.152*	0.123**	0.030
	(0.226)	(0.062)	(0.044)	(0.020)
Stock price included	−1.430*	0.515**	−0.500**	−0.016**
	(0.595)	(0.155)	(0.154)	(0.003)
Size of firm included	−0.117	0.042	−0.038	−0.004
	(0.323)	(0.120)	(0.110)	(0.010)
Government expenditures included	−1.055**	0.402**	−0.385**	−0.017**
	(0.309)	(0.108)	(0.106)	(0.004)
Dependent lag included	0.165	−0.057	0.050	0.007
	(0.184)	(0.063)	(0.055)	(0.008)
Trade flows included	0.487	−0.162	0.137*	0.024
	(0.280)	(0.085)	(0.068)	(0.019)
Data characteristics—aggregation level				
Industry-level data	−0.147	0.052	−0.046	−0.006
	(0.268)	(0.095)	(0.085)	(0.010)
Firm-level data	0.306	−0.104	0.090	0.014
	(0.286)	(0.093)	(0.078)	(0.016)
Data characteristics—time series vs. cross section				
Panel data	1.379**	−0.367**	0.234**	0.133*
	(0.280)	(0.056)	(0.039)	(0.052)
Cross-section data	1.084**	−0.338**	0.269**	0.069**
	(0.250)	(0.069)	(0.051)	(0.026)

Table 3. Continued.

	Ordered Probit Model 2	Marginal Effects Model 2		
		Significantly Negative	Insignificant	Significantly Positive
Spatial, temporal, and econometric issues				
Average year of sample	0.102**	−0.036**	0.032**	0.004
	(0.024)	(0.008)	(0.008)	(0.004)
Year of publication	−0.249**	0.088**	−0.078**	−0.010
	(0.031)	(0.011)	(0.010)	(0.009)
Less developed countries	−0.611**	0.232**	−0.216**	−0.015**
	(0.204)	(0.080)	(0.077)	(0.004)
OLS estimation	−0.571**	0.179**	−0.144**	−0.035*
	(0.164)	(0.046)	(0.035)	(0.015)
Instrumental variables estimation	−0.649**	0.227**	−0.200**	−0.027**
	(0.191)	(0.067)	(0.060)	(0.009)
Number of observations	767			
Prob (chi-squared)	0.000			
Log-likelihood	−481.9			
Log-likelihood restricted	−578.1			

[a] See the notes to Table 2.
* $p < 0.05$.
** $p < 0.01$.

capital less difficult, and increased possibilities for hedging. Another explanation may be the move away from heavy manufacturing in developed countries (the usual source of data), implying lower sunk costs as firms are more footloose. The results may, however, also be due to studies and data improving over the years. Arguably, we can only speculate as to the potential causes for the publication trend. On the one hand, the publication trend variable may mimic unobserved changes in the research design and the data and/or econometric techniques over time. On the other hand, we cannot preclude that the negative coefficient associated with the publication time trend variable truly identifies publication bias, in the sense that studies with negative estimates have in more recent times effectively had a higher chance of being accepted for publication. In this respect it is interesting to observe that the publication trend matches the development of theory on the investment-uncertainty relationship, which has focused more and more on a negative relationship as time progressed.

The results for the base specification (Table 2) are not entirely robust to the inclusion of the publication time trend variable. With respect to the sources of uncertainty, the increased relevance of profit uncertainty is notable. Using profit uncertainty now decreases the probability of finding a significantly negative effect and also substantially increases the probability of a significantly positive effect. The results for some of the control variables in primary models have changed as well, but most striking is the change in the relevance of the level of data aggregation. The differences between country-, industry-, and firm-level data are less substantial, not statistically significant, and the pattern has changed. However, the results still suggest that industry-level data produce more significantly negative estimates than firm-level data. Finally, the pattern related to differences in data type is similar to the pattern in model 1 but is more pronounced, and the probability of finding a negative relationship now appears substantially larger in developing countries than in developed countries.

The interpretation of the changes in empirical findings is ambiguous. As mentioned above, the publication trend variable may merely mimic and pick up changes in research methods and data over time, insofar as they are not captured by other explanatory variables in the model. Alternatively, if the publication trend variable truly picks up publication bias, the results in Table 3 better reflect the relevant sources of underlying effect size variation than those reported in Table 2. There is no direct evidence that supports either of these interpretations.

6. Conclusions

The impact of uncertainty on investment spending has been heavily debated since the early 1970s. The theoretical insights developed over the years provide an ambiguous picture as to the direction of the effect, and many intervening factors have been suggested over time. In this article we performed a meta-analysis to investigate whether the body of existing empirical evidence can provide more insight into the direction of the hypothesized relationship between investment and uncertainty.

Because most study results were incomparable, a transformation into elasticities was necessary. This only worked for a limited subset of the entire sample. Furthermore, the investment-uncertainty literature is primarily focused on the sign of the relationship and not on its magnitude. In order to make use of the full sample of study results while still focusing on the main issue in the literature, we decided to define a common and scale-free metric that does not include the magnitude of the relationship. Specifically, we focus on the direction and statistical significance of empirical estimates, and in our empirical analysis we estimate an ordered probit model using a categorical variable with three categories. The coefficients are transformed into marginal effects representing changes in the probability of finding a significantly negative, an insignificant, or a significantly positive study outcome. We estimate a base model as well as an alternative model that includes a publication time trend variable.

In view of the theoretical ambiguity regarding the direction of the relationship, our sample shows that very few studies actually find a significantly positive estimate. The marginal effects from the ordered probit analyses show that some study characteristics increase the probability of observing a significantly positive estimate; although, the effects are generally small. Ultimately, the empirical evidence supporting a positive investment-uncertainty relationship is limited. The marginal effects from the model without publication time trend furthermore show that there is substantial heterogeneity in the probabilities of observing a significantly negative and an insignificant study outcome. Differences in the relevant sources of uncertainty, model specifications, and data characteristics appear to be important sources of empirical variation in the underlying studies.

Uncertainty related to macroeconomic processes, such as inflation and exchange rate uncertainty, appears to be far less important for investment decisions than uncertainty related to sector- or firm-specific variation, such as uncertainty in output prices, sales, and profits. With respect to model specification it appears that excluding Tobin's Q and an accelerator variable, among others, produces substantially different results. Although we do not know the true underlying nature of the investment process, this result points to possible misspecifications in investment models. Furthermore, studies that use country-level data and studies that use industry- and firm-level data produce markedly different results. Since variation in investment between countries depends to a certain extent on issues that are difficult to account for in a model, it is likely that the observed differences are related to misspecifications in country-level studies. We find some evidence for the claim made in Pindyck (1993) that under industry-wide uncertainty the possibilities to disinvest are smaller than under firm-specific uncertainty. Although this may reflect a situation where there is no differential effect, it may also point to consequences of differences in data aggregation that cannot be disentangled from the Pindyck effect. The substantial difference between the short-run (time series) and long-run (cross section) effect of uncertainty is striking as well. The short-run effect appears to be negative, but the effect fades away as time progresses.

We also included year of publication among the explanatory variables in order to control for a possible publication time trend. The results from this model suggest that the probability of finding a significantly negative estimate is higher for more recent studies, while the actual underlying relationship appears to have become more insignificant over the years. Although most other findings remain unchanged, some results, such as those on the level of data aggregation, developing versus developed countries, and sources of uncertainty, are not robust to the inclusion of the publication time trend variable. One can obviously debate to what extent the publication time trend variable captures unobserved underlying real-world trends, unobserved changes in research design and data (for example, the use of microdata), or a true publication bias caused by increased odds of publication if a study documents a negative effect.

In conclusion, there is little empirical evidence for a positive investment-uncertainty relationship. Our results cannot, however, provide a definite answer to the question of whether uncertainty matters for investment spending. In some cases the findings suggest that potentially misspecified studies, such as those that omit an accelerator variable and those that do not control for endogeneity, decrease the probability of finding a significantly negative effect. In several other cases, however, potential misspecification, such as the use of country-level data or the use of the investment-to-capital ratio as the dependent variable, appears to increase the probability of finding a significantly negative effect. Moreover, if publication year does indeed represent an actual publication time trend, possibly caused by the development of theory over time, our results suggest that significantly negative study outcomes were more likely to be published as the research field matured.

Appendix

Table A1. Characteristics of the Studies Included in the Meta-Analysis (Ordered Chronologically)

Study	No. of Observations	Period	Region	Uncertainty Measure	Aggregation Level	Data Type
Dorfman and Heien (1989)	1	1970–1985	USA	B	F	C
Driver and Moreton (1991)	2	1978–1987	UK	F	I	T
Aizenman and Marion (1993)	8	1970–1985	LDC	B	C	C
Ferderer (1993a)	15	1978–1991	USA	F	F	T
Ferderer (1993b)	16	1969–1989	USA	B	C	T
Goldberg (1993)	174	1970–1989	USA	B	I	T
Huizinga (1993)	73	1954–1989	USA	B	I	T, C
Pindyck and Solimano (1993)	36	1960–1990	LDC	B	C	T, C
Serven and Solimano (1993)	4	1976–1988	LDC	B	C	P
Aizenman and Marion (1995)	7	1970–1993	LDC	B	C	C
Episcopos (1995)	5	1947–1992	USA	B	C	T
Price (1995)	3	1961–1992	UK	B	C	T
Bleaney (1996)	8	1980–1990	LDC	B	C	C
Ghosal and Loungani (1996)	35	1972–1989	USA	B	I	C
Leahy and Whited (1996)	64	1981–1987	USA	B	F	C
Price (1996)	3	1963–1994	UK	B	C	T
Bell and Campa (1997)	15	1977–1989	USA/Other	B	I	C
Glezakos and Nugent (1997)	4	1960–1990	USA	B	C	T
Serven (1997)	16	1970–1990	LDC	B	C	P
Brunetti and Weder (1998)	3	1974–1989	Various	B	C	C
Pattillo (1998)	3	1994–1995	Ghana	F	F	P
Serven (1998)	36	1970–1995	LDC	B	C	T, C, P
Aizenman and Marion (1999)	6	1970–1992	LDC	B	C	C, P
Darby et al. (1999)	3	1976–1996	Various	B	C	T
Goel and Ram (1999)	12	1974–1992	OECD	B	C	C

Table A1. Continued.

Study	No. of Observations	Period	Region	Uncertainty Measure	Aggregation Level	Data Type
Calcagnini and Saltari (2000)	11	1970–1995	Italy	F	C	T
Ghosal and Loungani (2000)	42	1958–1991	USA	B	I	C
Ogawa and Suzuki (2000)	36	1984–1993	Japan	B	F	P
Goel and Ram (2001)	6	1981–1992	OECD	B	C	T, P
Peeters (2001)	50	1983–1993	Spain/ Belgium	B	F	P
Temple, Urga, and Driver (2001)	16	1972–1992	UK	B	I	P
Bo (2002)	16	1984–1995	Netherlands	B	F	P
Lensink (2002)	1	1970–1997	Various	B	C	T, P
Henley, Carruth, and Dickerson (2003)	8	1975–1995	UK	B	F	P
Bo and Lensink (2005)	8	1984–1996	Netherlands	B	F	C
Lensink, van der Steen, and Sterken (2005)	21	1999	Netherlands	F	F	C

No. of observations: number of estimates provided by study. **Period**: time period to which study pertains. **Region**: region or country to which study pertains. **OECD**: study uses data for several OECD countries. **LDC**: Data are from less developed countries. **Uncertainty measure**: B=backward looking, F=forward looking. **Aggregation level**: C=country, I=industry, F=firm. **Data type**: T=time-series data, C=cross-section data, P=panel data.

References

(Note: Studies indicated with ■ have been included in the database)

Abel, Andrew B. 1983. Optimal investment under uncertainty. *American Economic Review* 73:228–33.

Abel, Andrew B., and Janice C. Eberly. 1999. The effects of irreversibility and uncertainty on capital accumulation. *Journal of Monetary Economics* 44:339–77.

Abreu, Maria, Henri L. F. de Groot, and Raymond J. G. M. Florax. 2005. A meta-analysis of beta-convergence: The legendary 2%. *Journal of Economic Surveys* 19:389–420.

Aizenman, Joshua, and Nancy P. Marion. 1993. Macroeconomic uncertainty and private investment. *Economics Letters* 41:207–10. ■

Aizenman, Joshua, and Nancy P. Marion. 1995. Volatility, investment and disappointment aversion. NBER Working Paper No. 5386. ■

Aizenman, Joshua, and Nancy P. Marion. 1999. Volatility and investment: Interpreting evidence from developing countries. *Economica* 66:157–79. ■

Bar-Ilan, Avner, and William C. Strange. 1999. The timing and intensity of investment. *Journal of Macroeconomics* 21:57–77.

Bell, Gregory K., and José M. Campa. 1997. Irreversible investments and volatile markets: A study of the chemical processing industry. *Review of Economics and Statistics* 79:79–87. ■

Bijmolt, Tammo H. A., and Rik G. M. Pieters. 2001. Meta-analysis in marketing when studies contain multiple measurements. *Marketing Letters* 12:157–69.

Bleaney, Michael F. 1996. Macroeconomic stability, investment and growth in developing countries. *Journal of Development Economics* 48:461–77. ■

Bo, Hong. 2001. Corporate investment under uncertainty in the Netherlands. Ph.D. dissertation, University of Groningen: the Netherlands,

Bo, Hong. 2002. Idiosyncratic uncertainty and firm investment. *Australian Economic Papers* 41:1–14. ■

Bo, Hong. 2006. An empirical examination of the hangover effect of irreversibility on investment. *Scottish Journal of Political Economy* 53:358–76.

Bo, Hong, and Robert Lensink. 2005. Is the investment-uncertainty relationship non-linear? An empirical analysis for the Netherlands. *Economica* 72:307–31. ■

Brunetti, Aymo, and Beatrice Weder. 1998. Investment and institutional uncertainty: A comparative study of different uncertainty measures. *Weltwirtschaftliches Archiv* 134:513–33. ■

Caballero, Ricardo J. 1991. On the sign of the investment-uncertainty relationship. *American Economic Review* 81:279–88.

Calcagnini, Giorgio, and Enrico Saltari. 2000. Real and financial uncertainty and investment decisions. *Journal of Macroeconomics* 22:491–514. ■

Carruth, Alan, Andrew P. Dickerson, and Andrew Henley. 2000. What do we know about investment under uncertainty? *Journal of Economic Surveys* 14:119–53.

Cuthbertson, Keith, and David Gasparro. 1995. Fixed investment decisions in UK manufacturing: The importance of Tobin's *Q*, output and debt. *European Economic Review* 39:919–41.

Darby, Julia, Andrew H. Hallett, Jonathan Ireland, and Laura Piscitelli. 1999. The impact of exchange rate uncertainty on the level of investment. *Economic Journal* 109:C5–C67. ■

de Dominicis, Laura, Raymond J. G. M. Florax, and Henri L. F. de Groot. 2008. Meta-analysis of the relationship between income inequality and economic growth. *Scottish Journal of Political Economy* 55:654–82.

de Mooij, Ruud A., and Sjef Ederveen. 2003. Taxation and foreign direct investment: A synthesis of empirical research. *International Tax and Public Finance* 10:673–93.

Dixit, Avinash K., and Robert S. Pindyck. 1994. *Investment under uncertainty*. Princeton, NJ: Princeton University Press.

Djankov, Simeon, and Peter Murrell. 2002. Enterprise restructuring in transition: A quantitative survey. *Journal of Economic Literature* 40:739–92.

Dorfman, Jeffrey H., and Dale Heien. 1989. The effects of uncertainty and adjustment costs on investment in the almond industry. *Review of Economics and Statistics* 71:263–74. ■

Driver, Ciaran, and David Moreton. 1991. The influence of uncertainty on UK manufacturing investment. *Economic Journal* 101:1452–59. ■

Episcopos, Athanasios. 1995. Evidence on the relationship between uncertainty and irreversible investment. *Quarterly Review of Economics and Finance* 35:41–51. ■

Favero, Carlo A., M. Hashem Pesaran, and Sunil Sharma. 1994. A duration model of irreversible oil investment: Theory and empirical evidence. *Journal of Applied Econometrics* 9:S95–S112.

Ferderer, J. Peter. 1993a. Does uncertainty affect investment spending? *Journal of Post Keynesian Economics* 16:19–35. ■

Ferderer, J. Peter. 1993b. The impact of uncertainty on aggregate investment spending: An empirical analysis. *Journal of Money, Credit, and Banking* 25:30–48. ■

Ghosal, Vivek. 1991. Demand uncertainty and the capital-labor ratio: Evidence from the U.S. manufacturing sector. *Review of Economics and Statistics* 73:157–61.

Ghosal, Vivek. 1995. Input choices under price uncertainty. *Economic Inquiry* 33:142–58.

Ghosal, Vivek, and Prakash Loungani. 1996. Product market competition and the impact of price uncertainty on investment: Some evidence from U.S. manufacturing industries. *Journal of Industrial Economics* 44:217–28. ■

Ghosal, Vivek, and Prakash Loungani. 2000. The differential impact of uncertainty on investment in small and large businesses. *Review of Economics and Statistics* 82:338–49. ■

Glezakos, Constantine, and Jeffrey B. Nugent. 1997. Relative price variability, inflation rate uncertainty, and postwar investment of the United States. *Journal of Post Keynesian Economics* 19:181–94. ■

Goel, Rajeev K., and Rati Ram. 1999. Variations in the effect of uncertainty on different types of investment: An empirical investigation. *Australian Economic Papers* 38:481–92. ■

Goel, Rajeev K., and Rati Ram. 2001. Irreversibility of R&D investment and the adverse effect of uncertainty: Evidence from the OECD countries. *Economics Letters* 71:287–91. ■

Goldberg, Linda S. 1993. Exchange rates and investment in United States industry. *Review of Economics and Statistics* 75:575–88. ■

Goldfarb, Robert S. 1995. The economist-as-audience needs a methodology of plausible inference. *Journal of Economic Methodology* 2:201–22.

Green, Christopher J., Robert Lensink, and Victor Murinde. 2001. Demand uncertainty and the capital-labour ratio in Poland. *Emerging Markets Review* 2:184–97.

Greene, William H. 2003. *Econometric analysis*. 5th edition. Upper Saddle River, NJ: Prentice Hall International, Inc.

Hartman, Richard. 1972. The effects of price and cost uncertainty on investment. *Journal of Economic Theory* 5:258–66.

Hedges, Larry V. 1992. Modeling publication selection effects in meta-analysis. *Statistical Science* 7:246–55.

Henley, Andrew, Alan Carruth, and Andrew P. Dickerson. 2003. Industry-wide versus firm-specific uncertainty and investment: British company panel data evidence. *Economics Letters* 78:87–92. ■

Huizinga, John. 1993. Inflation uncertainty, relative price uncertainty, and investment in U.S. manufacturing. *Journal of Money, Credit, and Banking* 25:521–57. ■

Hurn, A. Stan, and Robert E. Wright. 1994. Geology or economics? Testing models of irreversible investment using North Sea oil data. *Economic Journal* 104:363–71.

Jorgenson, Dale W. 1971. Econometric studies of investment behavior: A survey. *Journal of Economic Literature* 9:1111–47.

Kahneman, Daniel, and Amos Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47:263–91.

Koetse, Mark J., Henri L. F. de Groot, and Raymond J. G. M. Florax. 2006. The impact of uncertainty on investment spending: A meta-analysis. TI Discussion Paper No. 06-060/3, Amsterdam: Tinbergen Institute.

Koetse, Mark J., Arno J. van der Vlist, and Henri L. F. de Groot. 2006. The impact of perceived expectations and uncertainty on firm investment. *Small Business Economics* 26:365–76.

Kulatilaka, Nalin, and Enrico C. Perotti. 1998. Strategic growth options. *Management Science* 44:1021–31.

Leahy, John V., and Toni M. Whited. 1996. The effect of uncertainty on investment: Some stylized facts. *Journal of Money, Credit, and Banking* 28:64–83. ■

Lensink, Robert. 2002. Is the uncertainty-investment link non-linear? Empirical evidence for developed economies. *Weltwirtschaftliches Archiv* 138:131–47. ■

Lensink, Robert, Paul van der Steen, and Elmer Sterken. 2005. Uncertainty and growth of the firm. *Small Business Economics* 24:381–91. ■

Nakamura, Tamotsu. 1999. Risk aversion and the uncertainty-investment relationship: A note. *Journal of Economic Behavior and Organization* 38:357–63.

Nijkamp, Peter, and Jacques Poot. 2004. Meta-analysis of the effect of fiscal policies on long-run growth. *European Journal of Political Economy* 20:91–124.

Ogawa, Kazuo, and Kazuyuki Suzuki. 2000. Uncertainty and investment: Some evidence from the panel data of Japanese manufacturing firms. *Japanese Economic Review* 51:170–92. ■

Pattillo, Catherine. 1998. Investment, uncertainty, and irreversibility in Ghana. *IMF Staff Papers* 45:522–53. ■

Peeters, Marga. 2001. Does demand and price uncertainty affect Belgian and Spanish corporate investment? *Louvain Economic Review* 67:119–39. ■

Pindyck, Robert S. 1982. Adjustment costs, uncertainty, and the behavior of the firm. *American Economic Review* 72:415–27.

Pindyck, Robert S. 1991. Irreversibility, uncertainty, and investment. *Journal of Economic Literature* 29:1110–48.

Pindyck, Robert S. 1993. A note on competitive investment under uncertainty. *American Economic Review* 83:273–77.

Pindyck, Robert S., and Andres Solimano. 1993. Economic instability and aggregate investment. *NBER Macroeconomics Annual* 8:259–303. ■

Poot, Jacques. 2000. A synthesis of empirical research on the impact of government on long-run growth. *Growth and Change* 31:516–46.

Price, Simon. 1995. Aggregate uncertainty, capacity utilization and manufacturing investment. *Applied Economics* 27:147–54. ■

Price, Simon. 1996. Aggregate uncertainty, investment and asymmetric adjustment in the UK manufacturing sector. *Applied Economics* 28:1369–79. ■

Roberts, Colin J., and Tom D. Stanley. 2005. *Meta-regression analysis: Issues of publication bias in economics*. Oxford: Blackwell.

Rose, Andrew K., and Tom D. Stanley. 2005. A meta-analysis of the effect of common currencies on international trade. *Journal of Economic Surveys* 19:347–65.

Rosenberger, Randall S., and Tom D. Stanley. 2006. Measurement, generalization, and publication: Sources of error in benefit transfers and their management. *Ecological Economics* 60:372–78.

Saltari, Enrico, and Davide Ticchi. 2005. Risk aversion and the investment-uncertainty relationship: A comment. *Journal of Economic Behavior and Organization* 56:121–25.

Serven, Luis. 1997. Irreversibility, uncertainty, and private investment: Analytical issues and some lessons for Africa. *Journal of African Economies* 6:229–68. ■

Serven, Luis. 1998. Macroeconomic uncertainty and private investment in developing countries: An empirical investigation. Policy Research Working Paper No. 2035. Washington D.C.: The World Bank. ■

Serven, Luis, and Andres Solimano. 1993. Debt crisis, adjustment policies and capital formation in developing countries: Where do we stand? *World Development* 21:127–40. ■

Stanley, Tom D. 1998. New wine in old bottles: A meta-analysis of Ricardian equivalence. *Southern Economic Journal* 64:713–27.

Stanley, Tom D. 2001. Wheat from chaff: Meta-analysis as quantitative literature review. *Journal of Economic Perspectives* 15:131–50.

Stanley, Tom D. 2008. Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection. *Oxford Bulletin of Economics and Statistics* 70:103–27.

Temple, Paul, Giovanni Urga, and Ciaran Driver. 2001. The influence of uncertainty on investment in the UK: A macro or micro phenomenon? *Scottish Journal of Political Economy* 48:361–82. ■

Tobin, James. 1969. A general equilibrium approach to monetary theory. *Journal of Money, Credit, and Banking* 1:15–29.

Weichselbaumer, Doris, and Rudolf Winter-Ebmer. 2005. A meta-analysis of the international gender wage gap. *Journal of Economic Surveys* 19:479–511.